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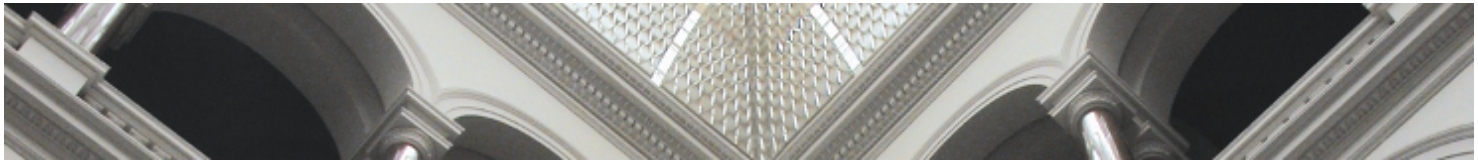
Designing Recurrent Neural Networks for Explainability

Pattarawat Chormai | Master's thesis supervised by Prof. Klaus-Robert Müller & Dr. Grégoire Montavon



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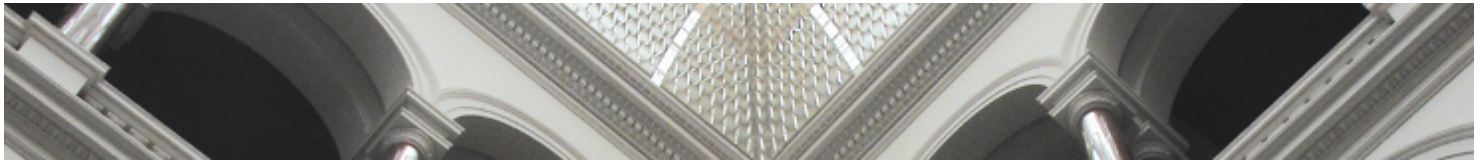
Motivation

- Impact of the architecture of RNNs on explainability
- Do deep RNNs have more explainable predictions?
- Are there ways to make RNNs more explainable?



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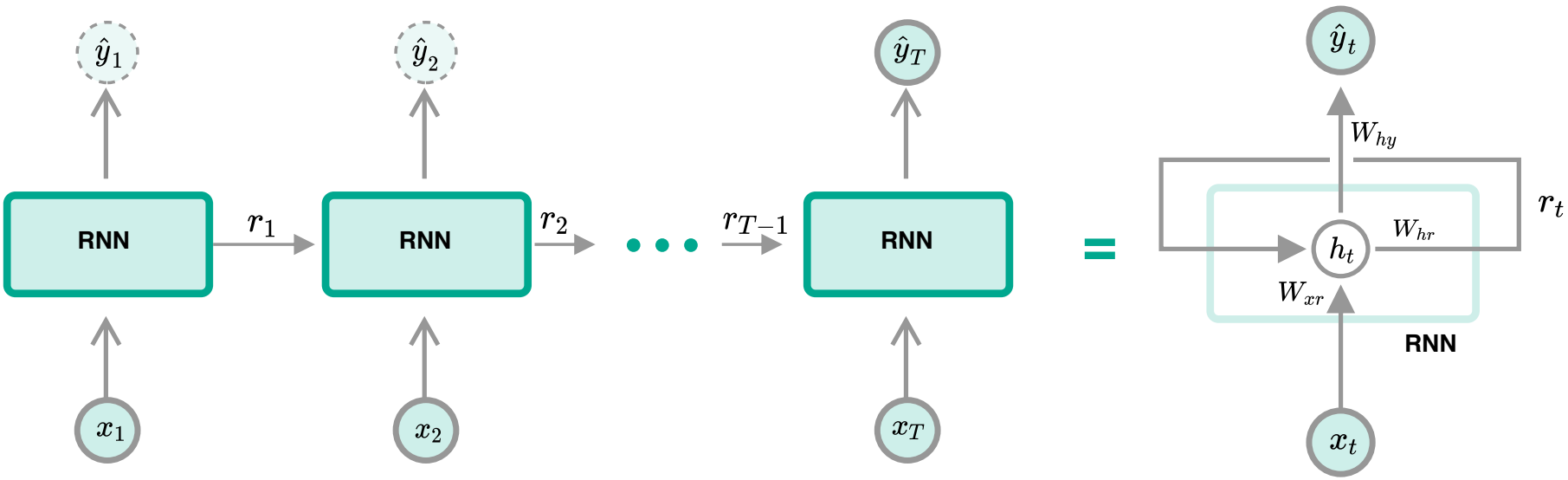
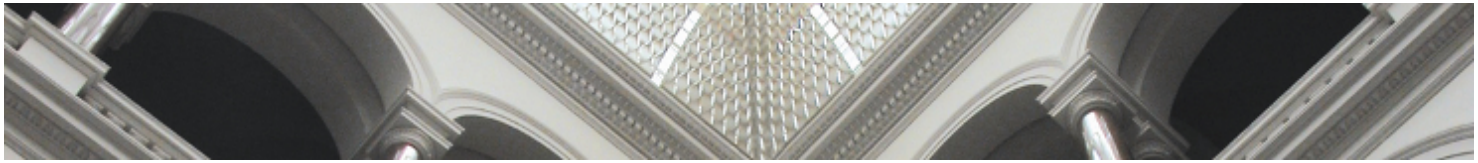
Recurrent Neural Networks (RNNs)

– **Successful applications:**

▷ machine translation [WSC+16], image captioning [VTBE15, VSP+17]





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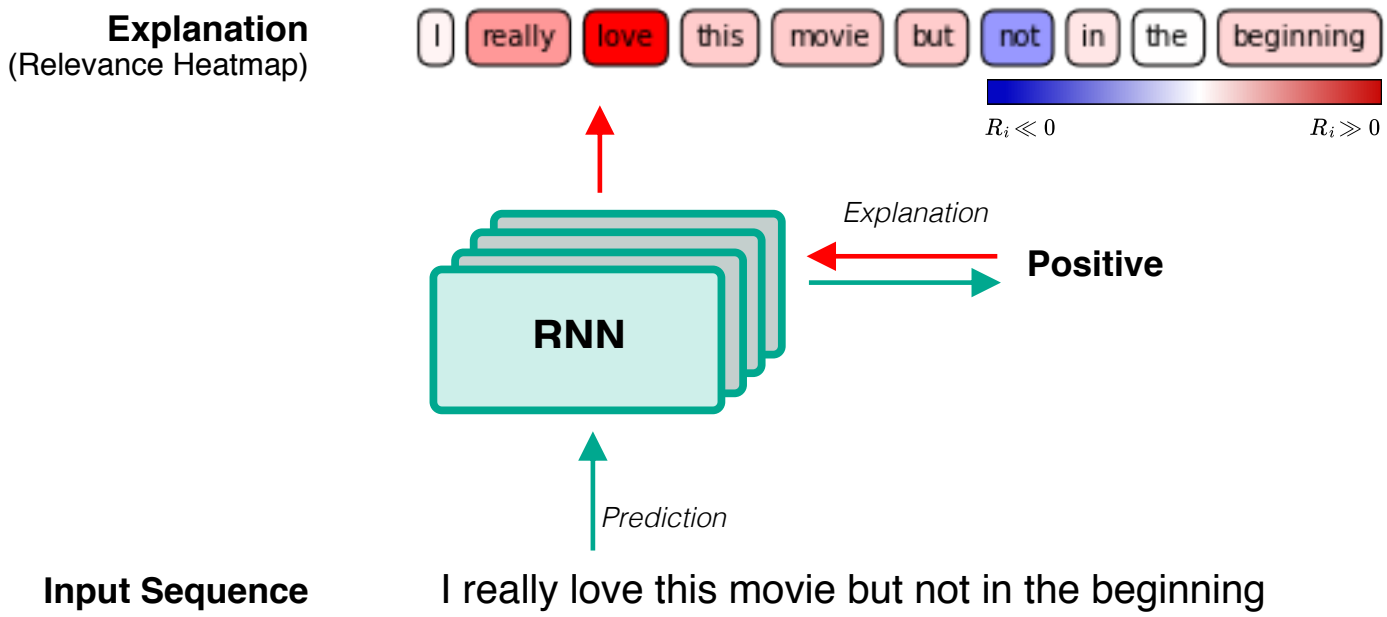
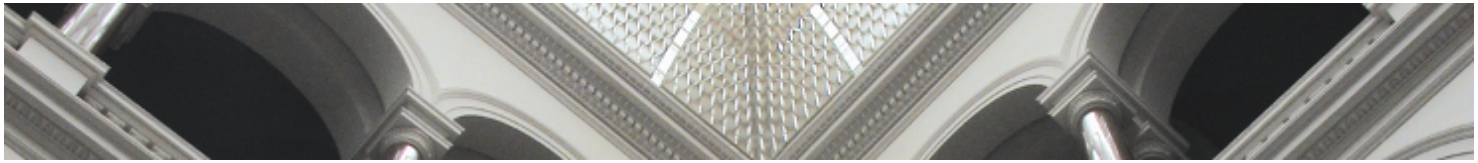
Explainability

- Ability to provide **sensible explanation** towards how input associates to a certain prediction
- **Analogy:** why does the RNN classify this text as a positive review?





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Explanation Methods I

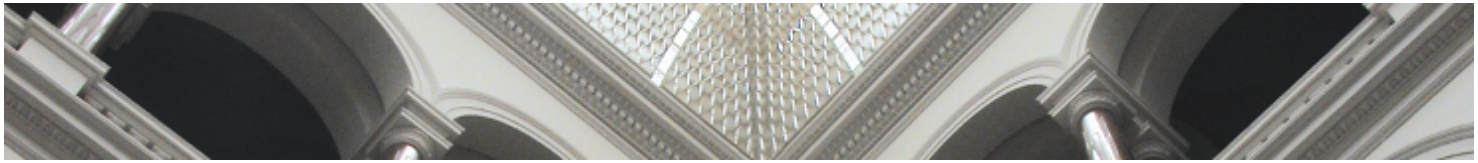
1. Sensitivity Analysis [SVZ13] (SA)

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

2. Guided Backprop [SDBR15] (GB)

   - Developed for explaining **ReLU**-based CNNs

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



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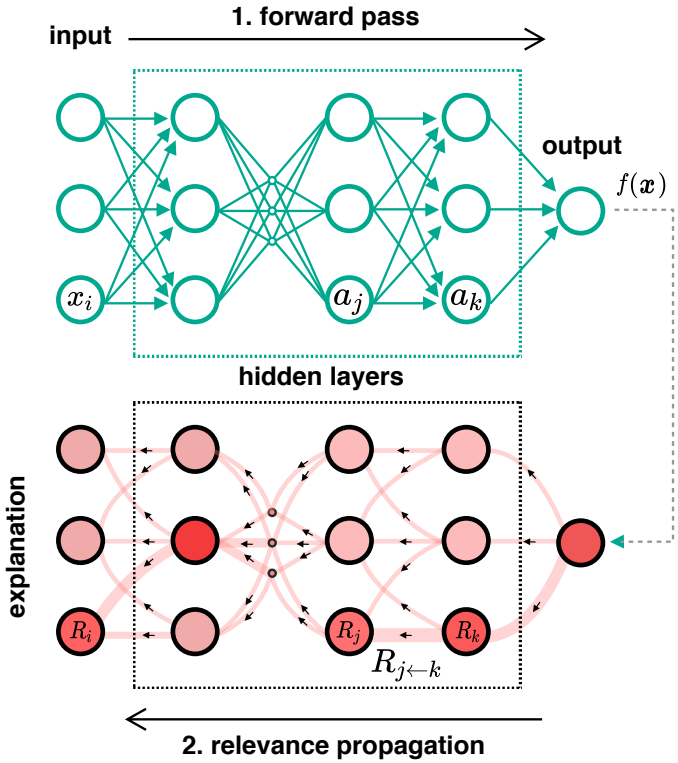
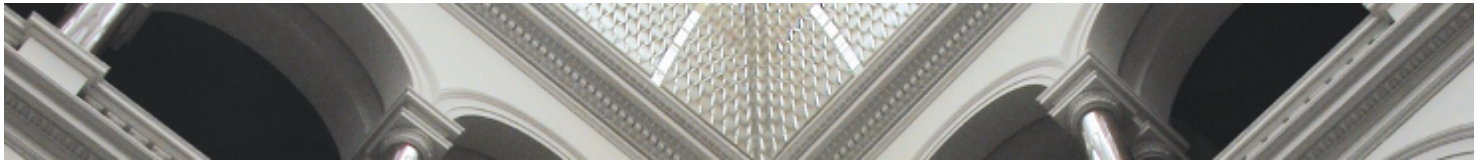
Explanation Methods II

3. Layer-wise Relevance Propagation [BML+16] (LRP)
   - Distributing relevance based on **neurons' activities**



LRP-$\alpha\beta$ rule:

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



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Explanation Methods III

4. Deep Taylor Decomposition [MLB$^+$17] (DTD)
   - LRP's theoretical view for explaining **ReLU-based** architectures

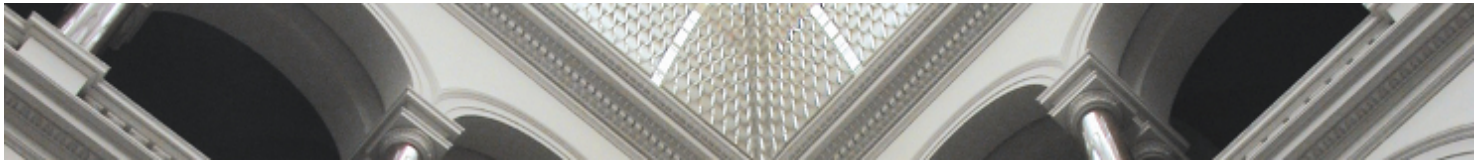
$$R_k = R_k\Big|_{\{\tilde{a}_j\}_j} + \sum_j \frac{\partial R_k}{\partial a_j}\Big|_{\{\tilde{a}_j\}_j} (a_j - \tilde{a}_j) + \xi_k \qquad \text{(Taylor expansion)}$$

   - Two important propagation rules:
     – z^+ for $a_j \in \mathbb{R}^+$ (LRP-$\alpha_1\beta_0$)

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

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

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



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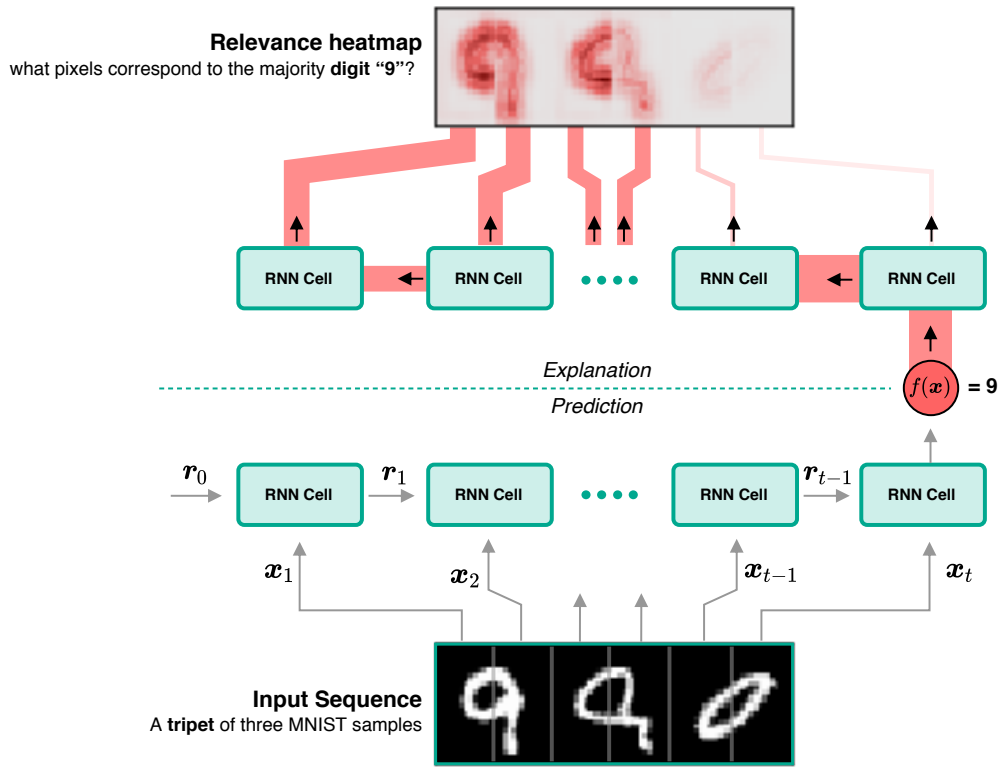
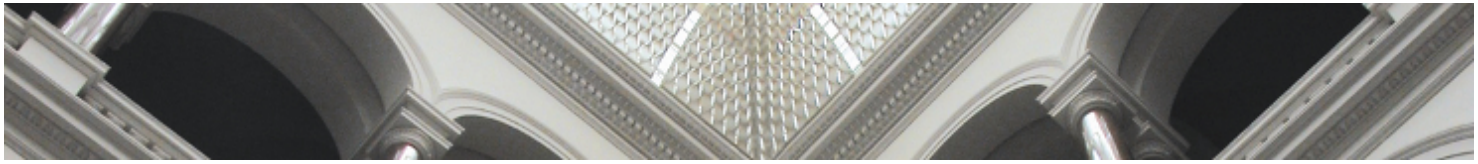
Experimental Setup

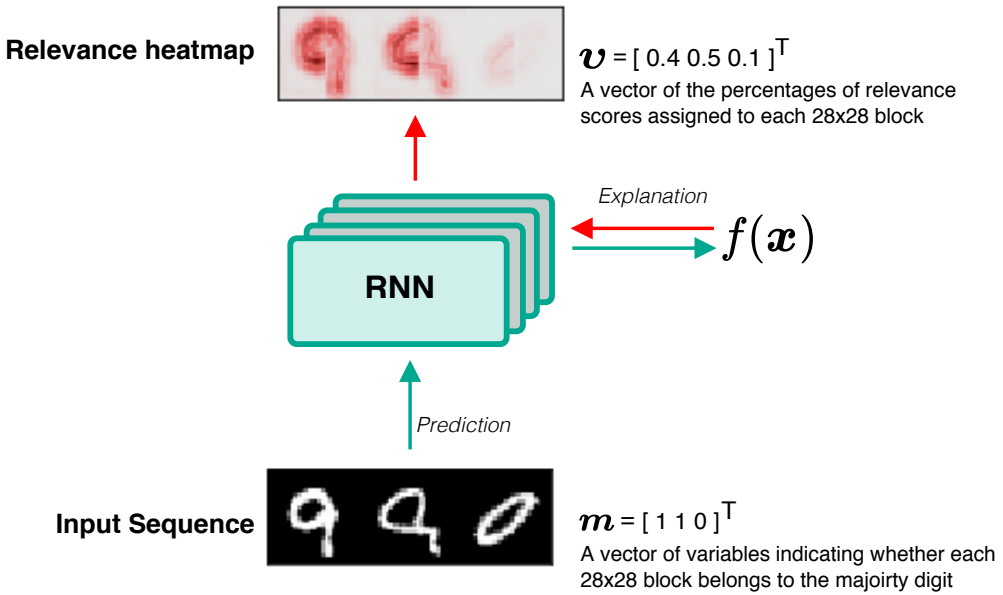
- **Problem:** Majority-Sample Sequence Classification (MNIST-MAJ, FashionMNIST-MAJ)
  - ▷ Sequence length: **12** $\left(\{\boldsymbol{x}_t \in \mathbb{R}^{28\times 7}\}_{t=1}^{12}\right)$
  - ▷ Minimum accuracy 98% for MNIST-MAJ and 89% for FashionMNIST-MAJ





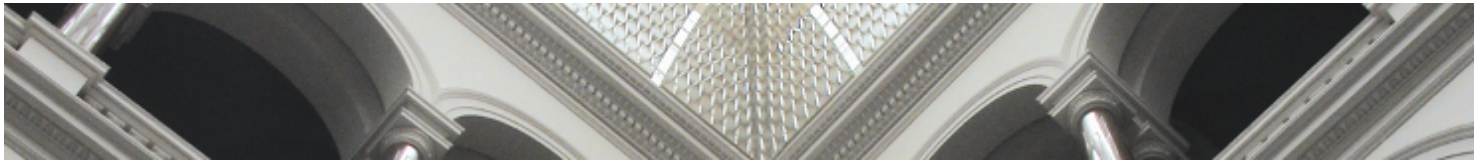
Experimental Setup

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

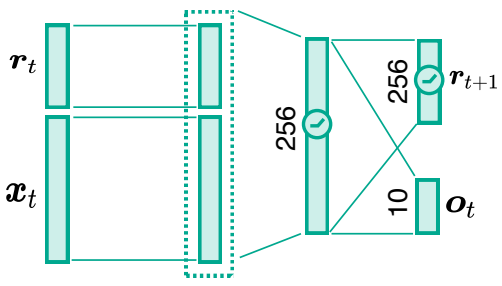


Heatmap Quality

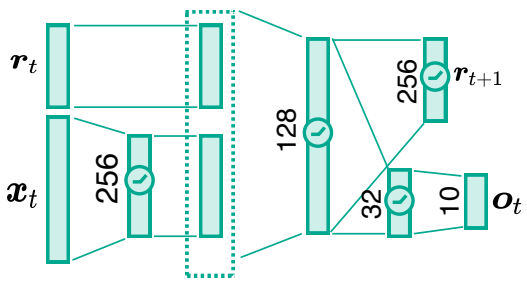
$$\cos(\boldsymbol{m}, \boldsymbol{v}) = \frac{\boldsymbol{m}^T \boldsymbol{v}}{\|\boldsymbol{m}\| \|\boldsymbol{v}\|}$$



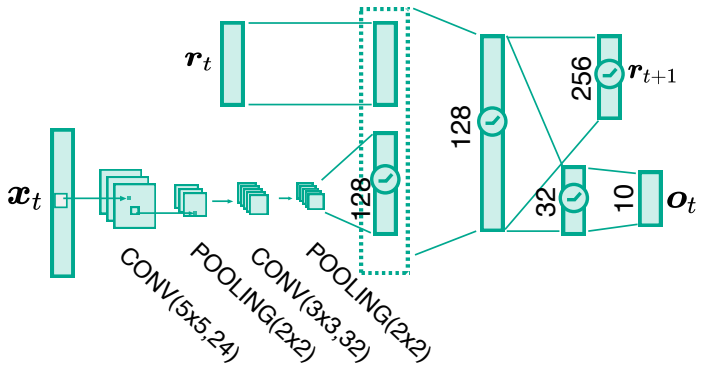
Experiment 1: Standard RNN Architectures



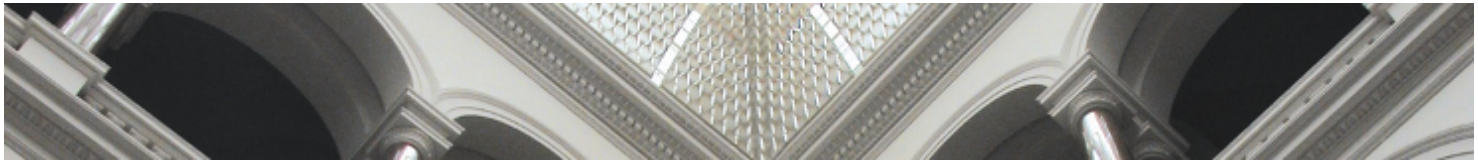
Shallow



Deep



ConvDeep



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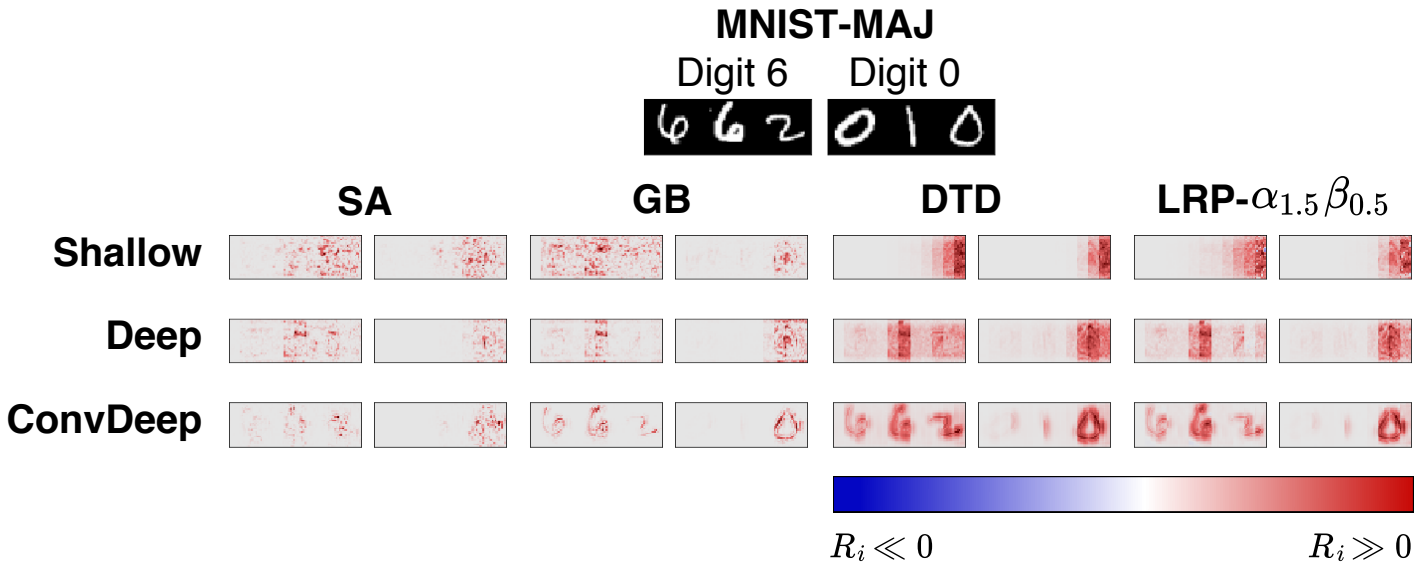
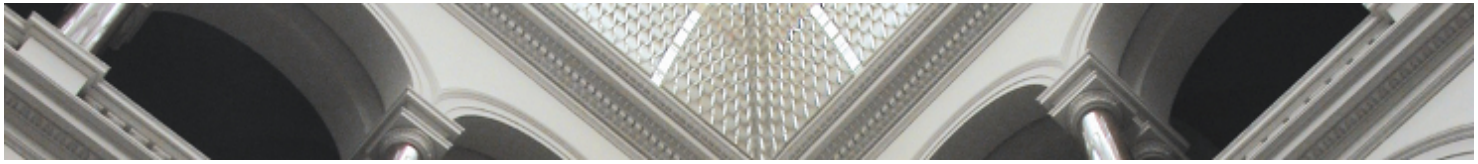
Experiment 1: Standard RNN Architectures

Sample Relevance Heatmaps





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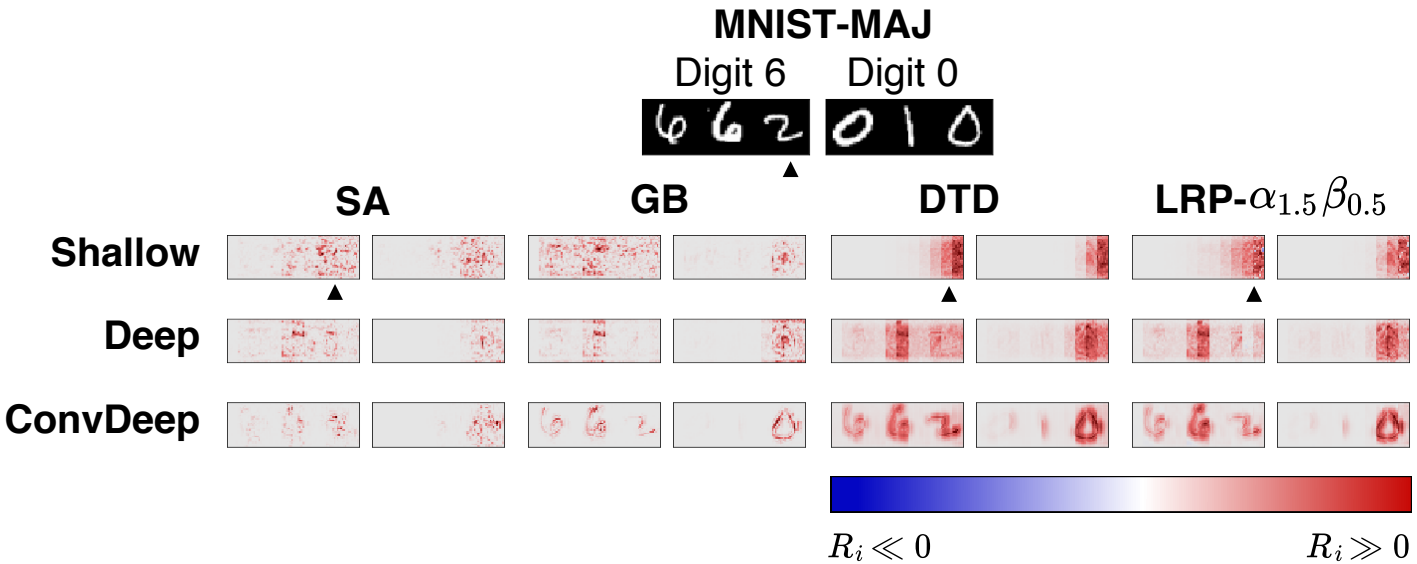

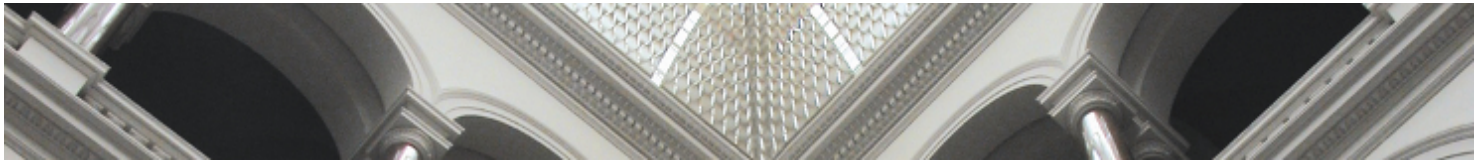

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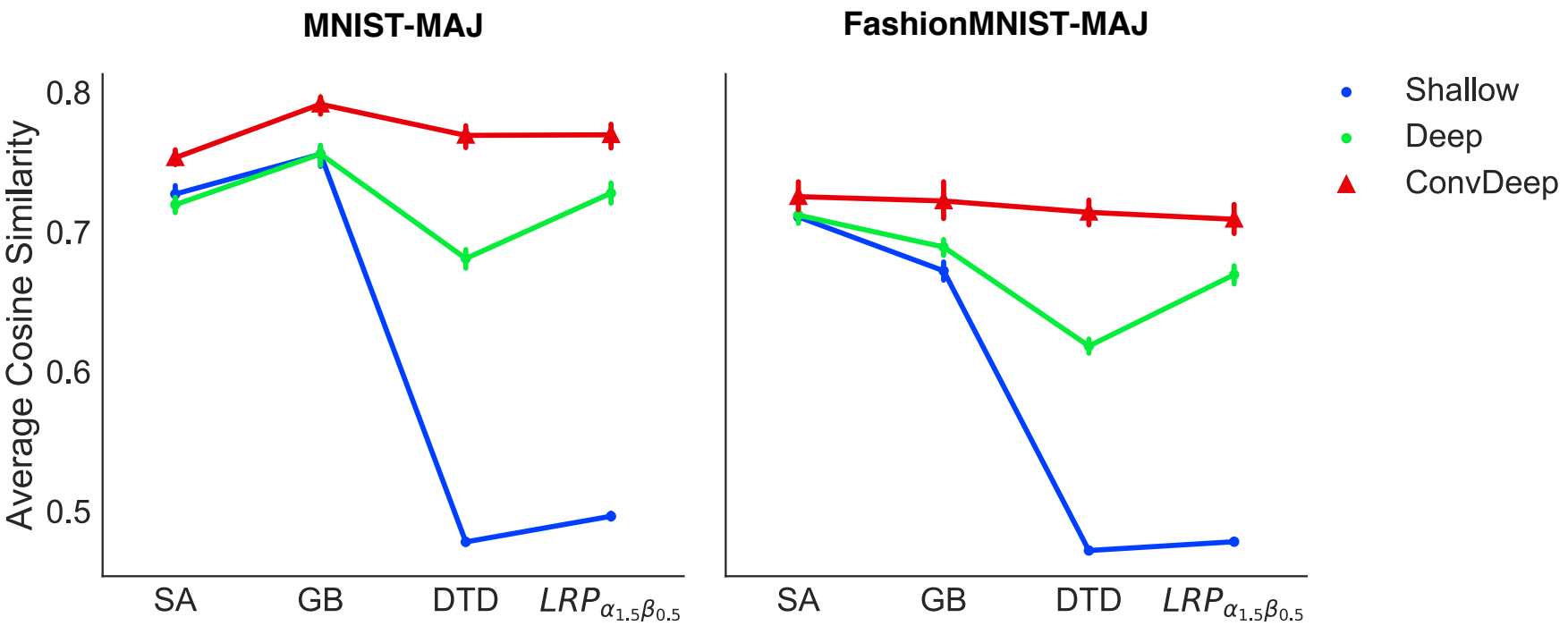
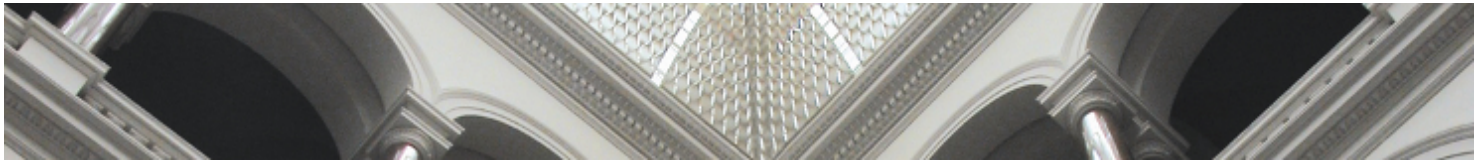
Experiment 1: Standard RNN Architectures

Cosine Similarity Evaluation





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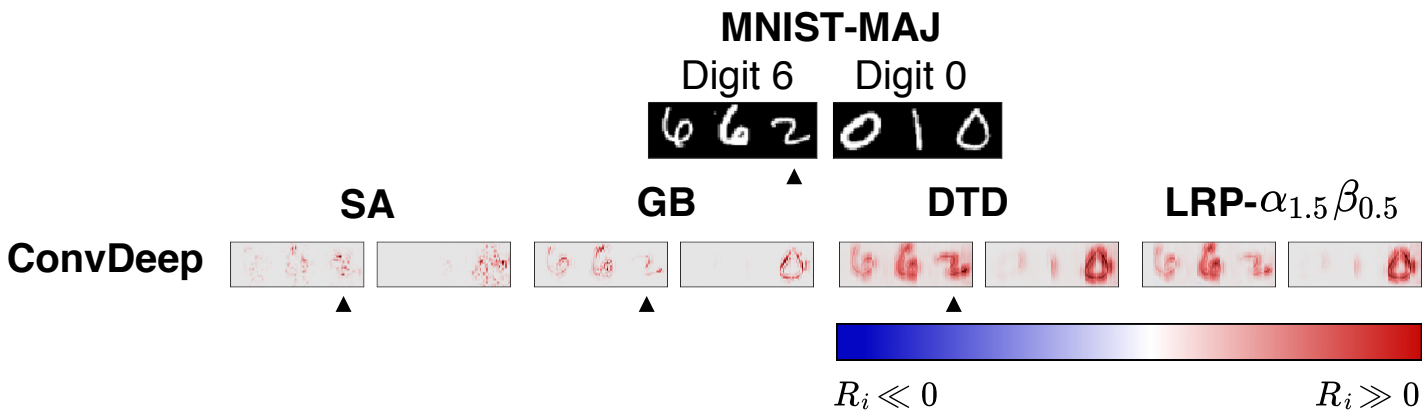
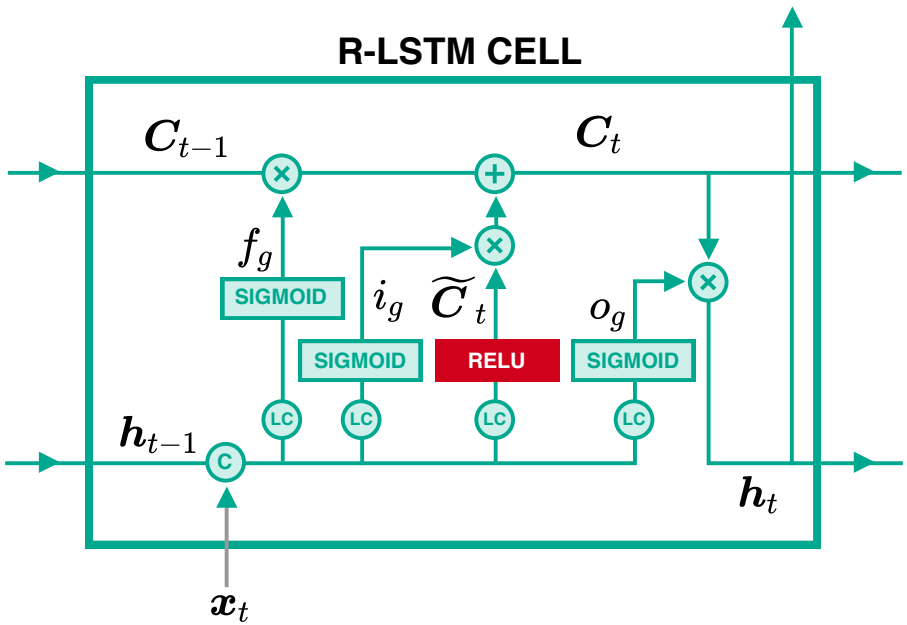
Experiment 2: More Explainable Models

Motivation: addressing the improper relevance assignment

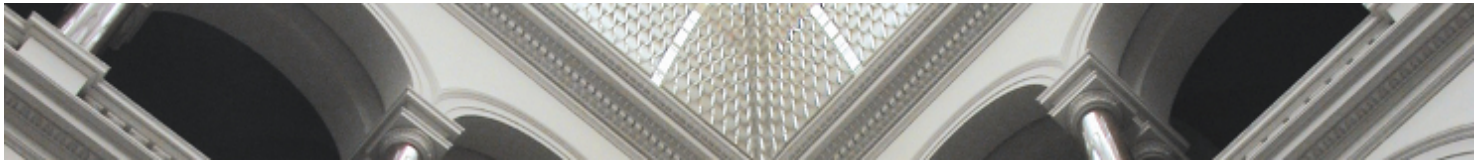


Experiment 2: More Explainable Models

1. LSTM [HS97]
   — Ignore gating neurons during explaining [AMMS17]
   — Replace tanh by ReLU (R-LSTM)

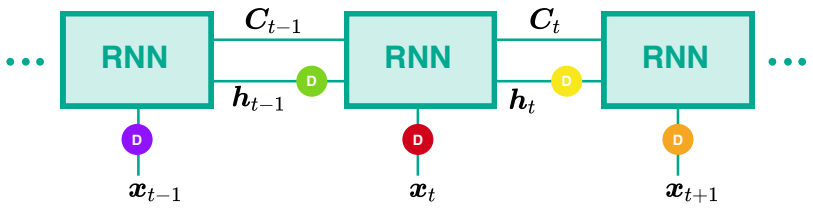


C Vector concatenation LC Linear combination ⊗ Element-wise multiplication ⊕ Element-wise addition

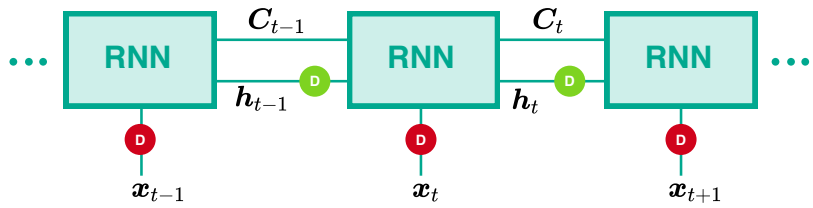


Experiment 2: More Explainable Models

1. LSTM [HS97]
2. Stationary Dropout (*Variational Recurrent* [GG16])

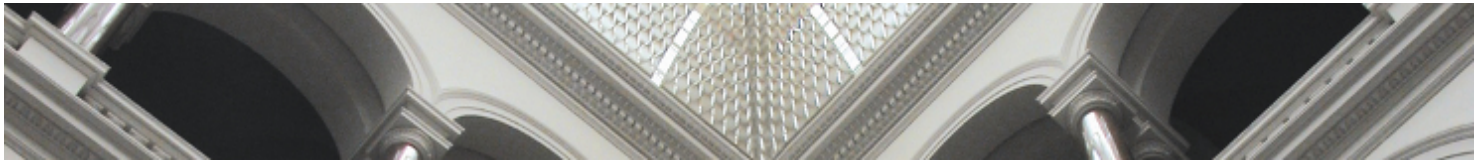


Naive Dropout



Stationary Dropout (-SD)

- Keras(2.2.4) : default behvariour for recurrent layers
- TensorFlow(r1.12): need to specify **variational_recurrent=True**



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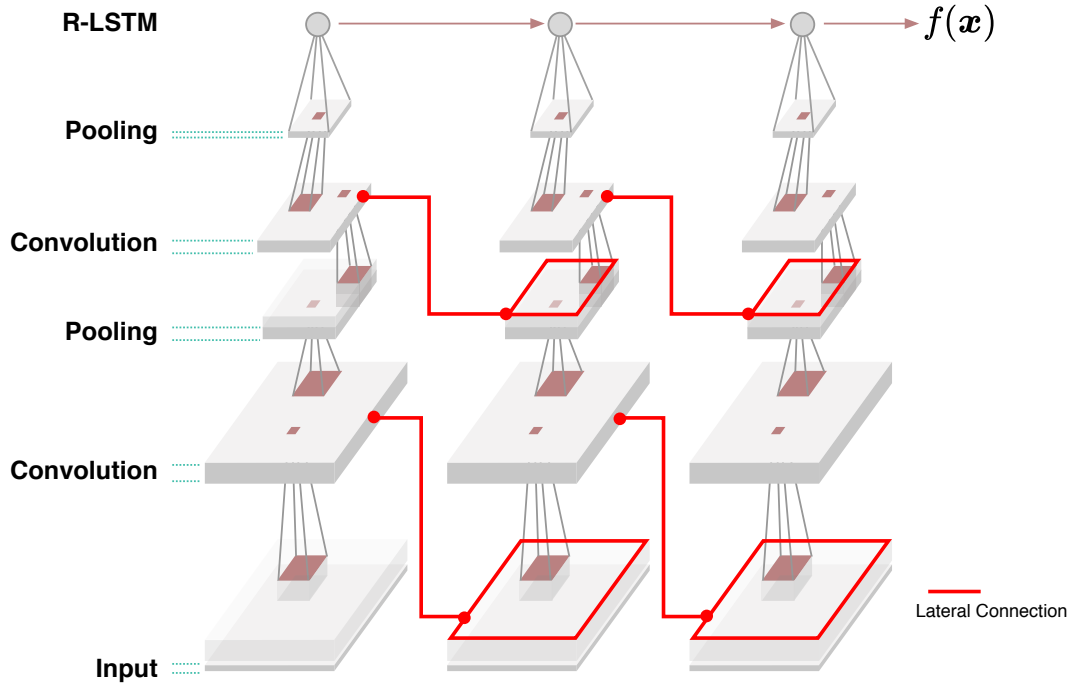
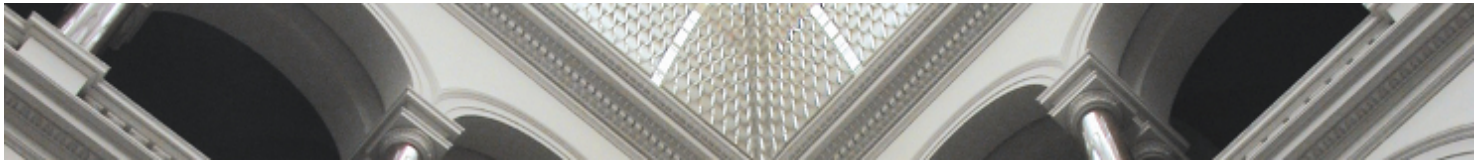
Experiment 2: More Explainable Models

1. LSTM [HS97]
2. Stationary Dropout (*Variational Recurrent* [GG16])
3. Lateral connections for convolutional layers (Conv^{+})





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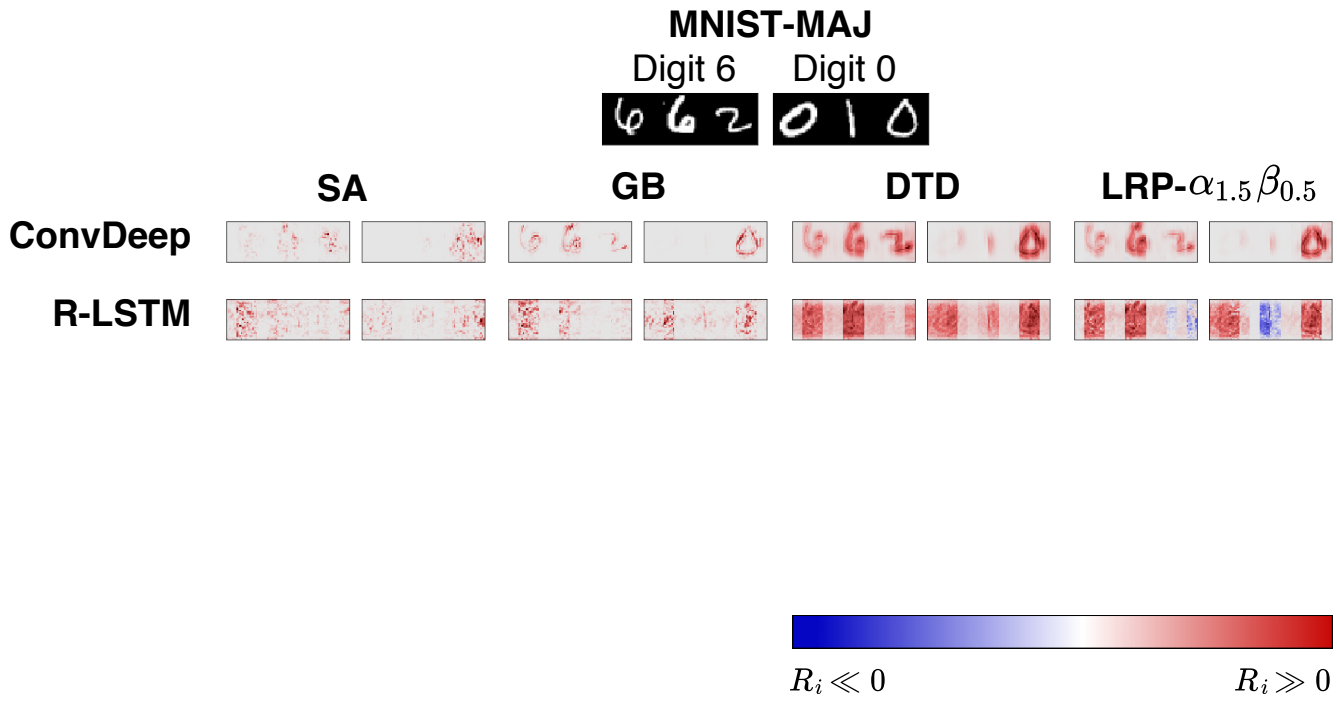
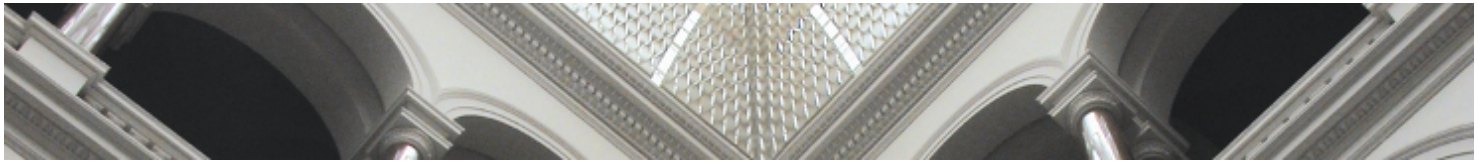
Experiment 2: More Explainable Models

Sample Relevance Heatmaps





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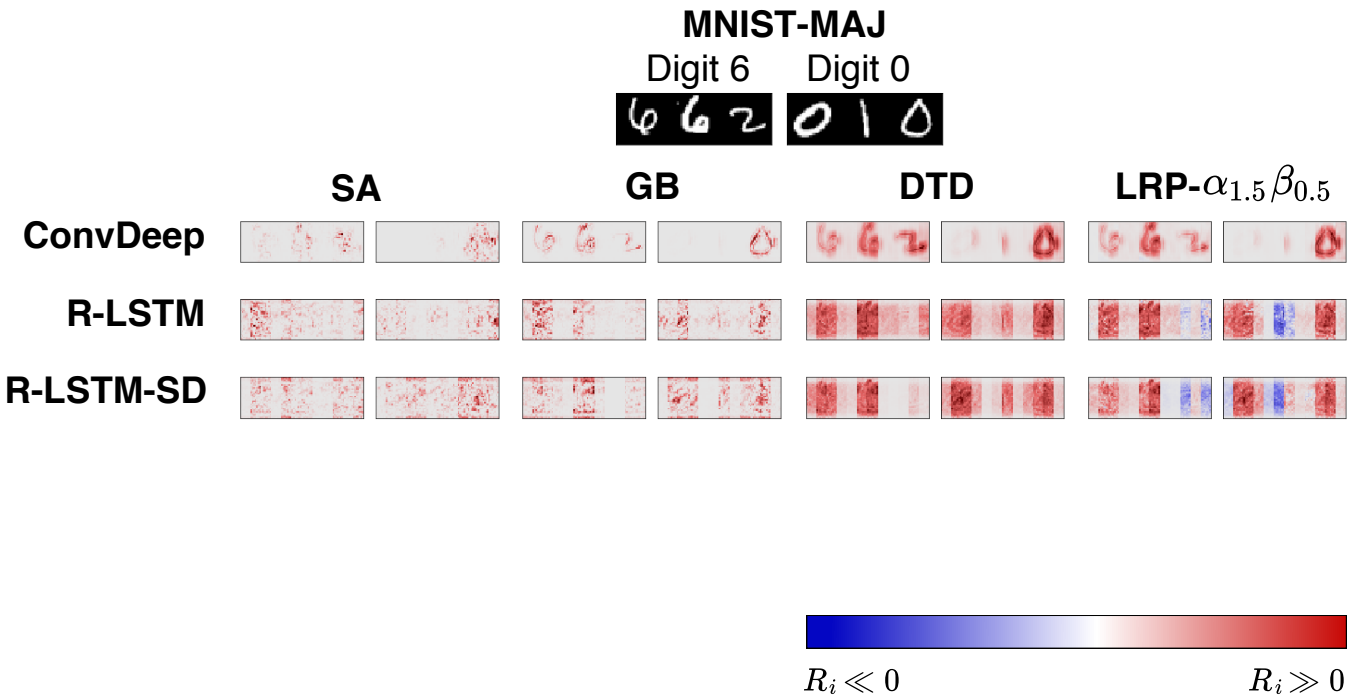

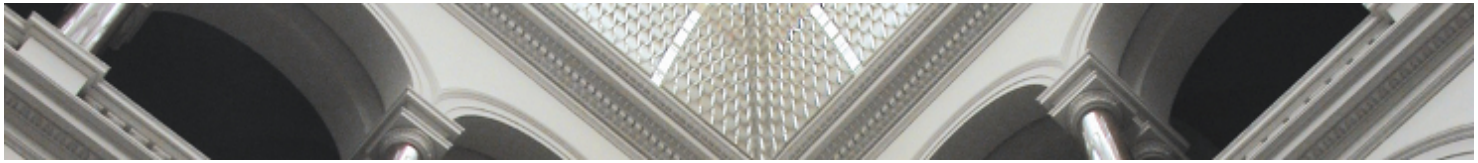

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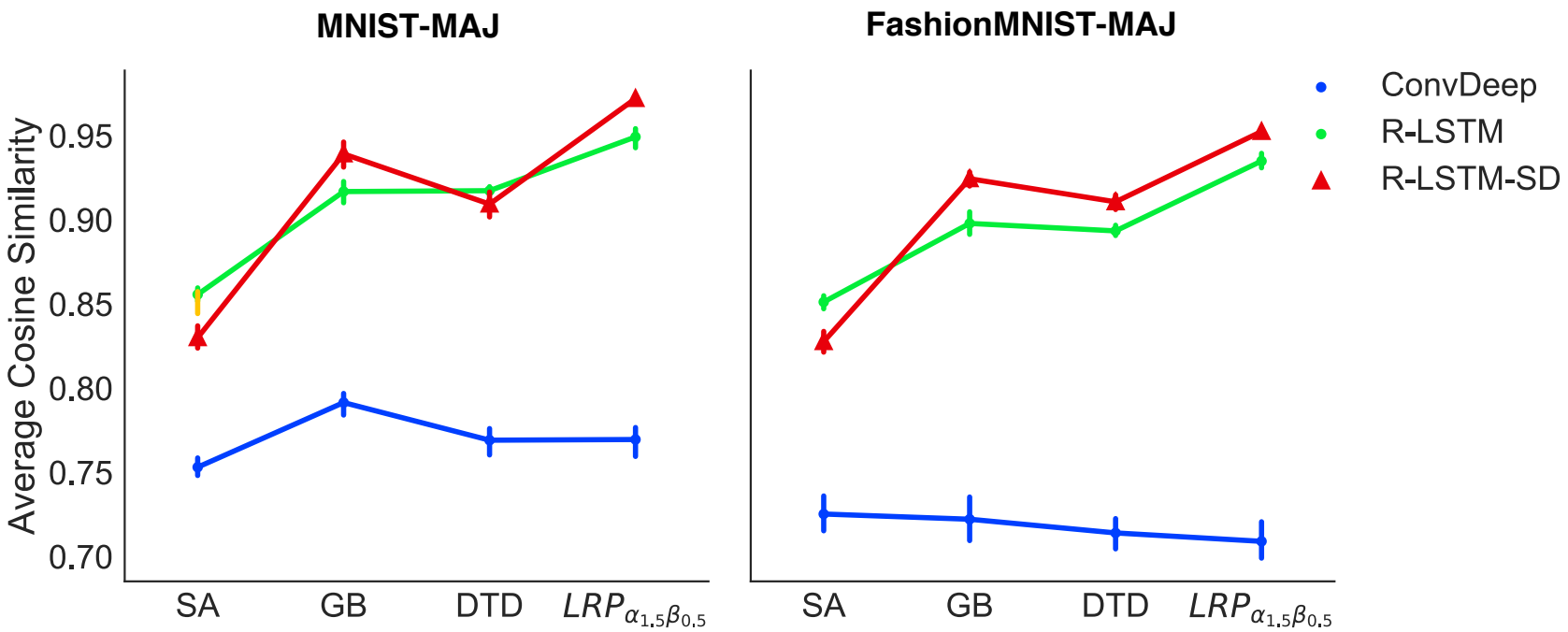
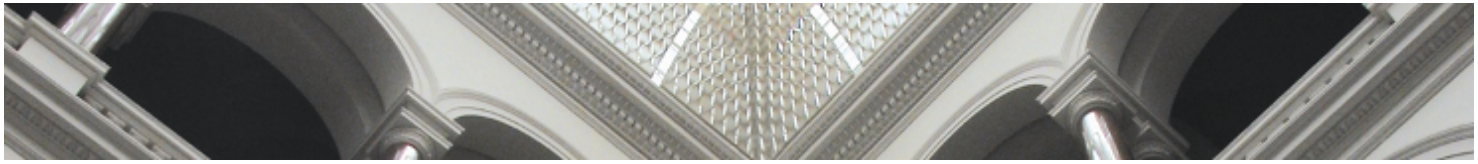
Cosine Similarity Evaluation





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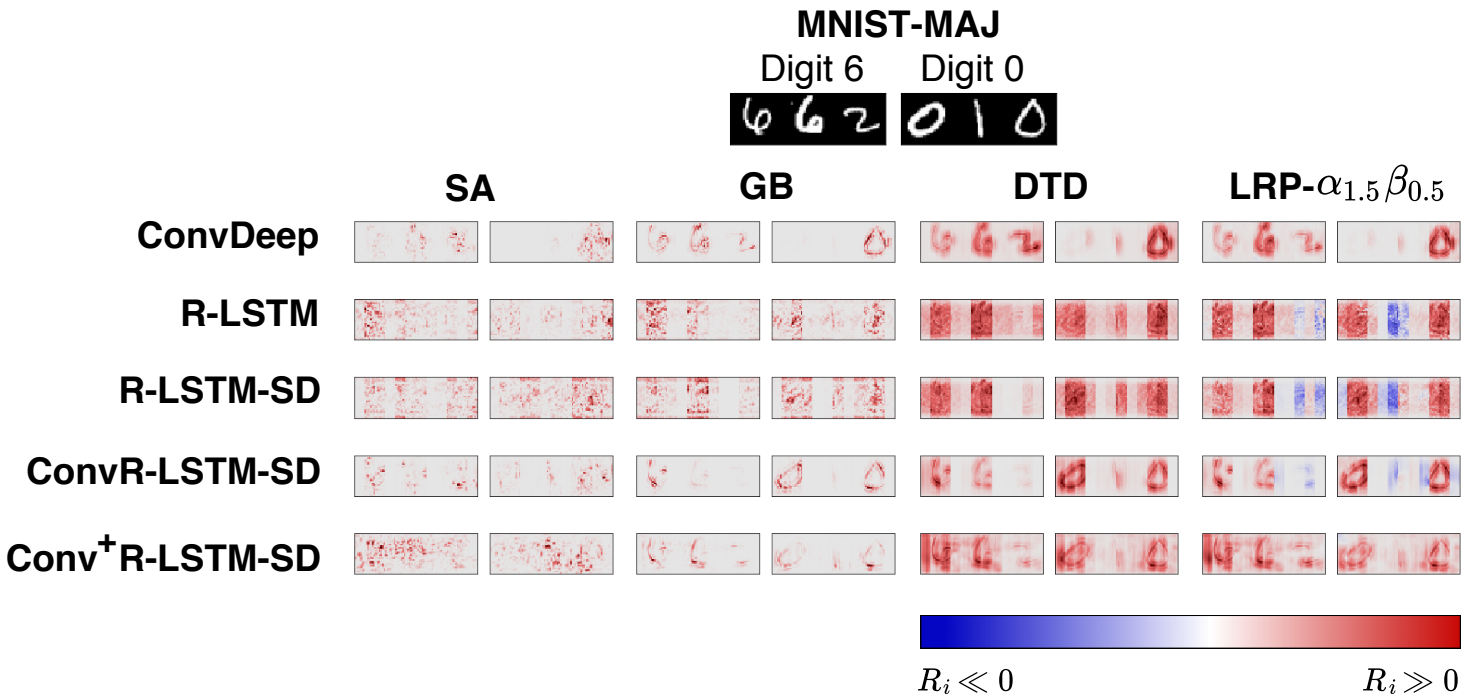

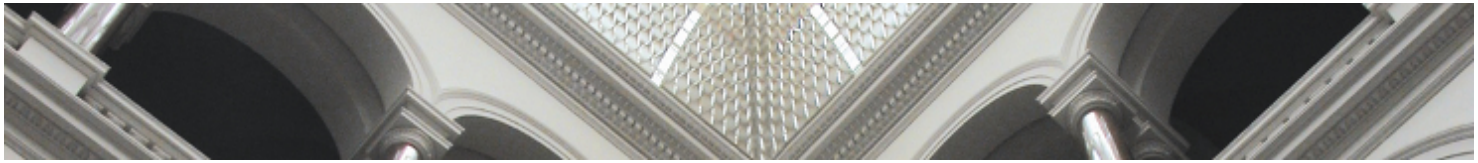

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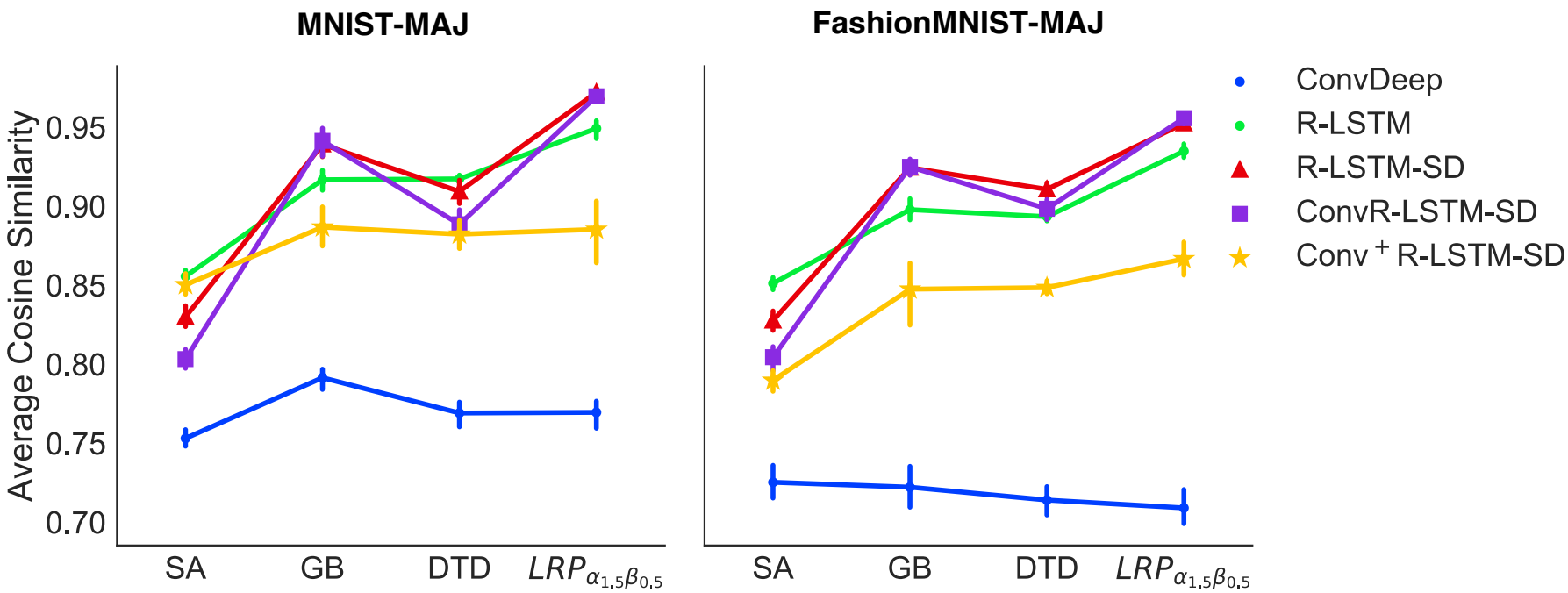

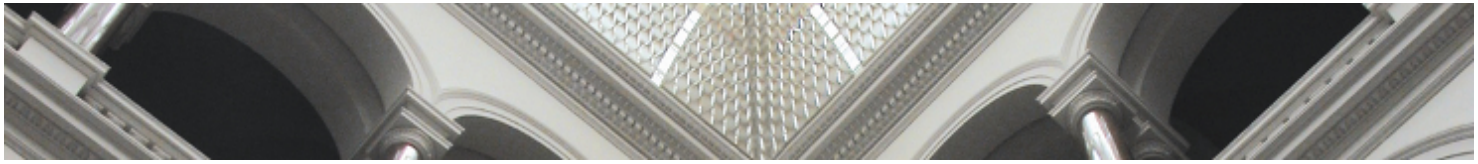

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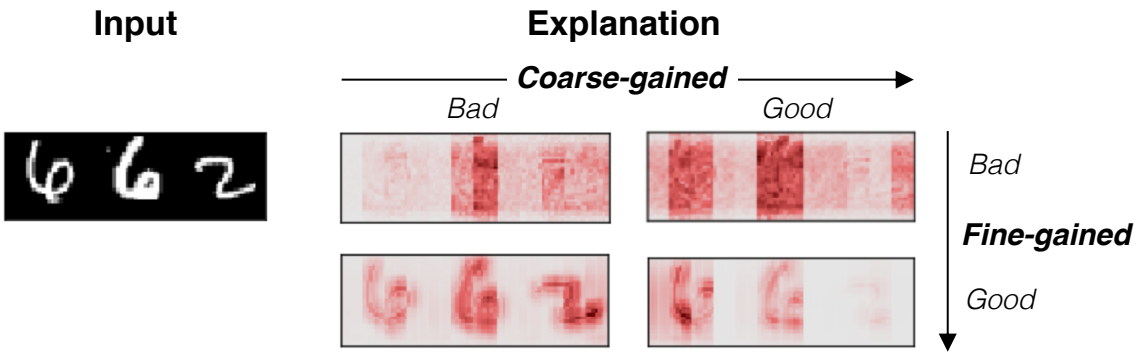
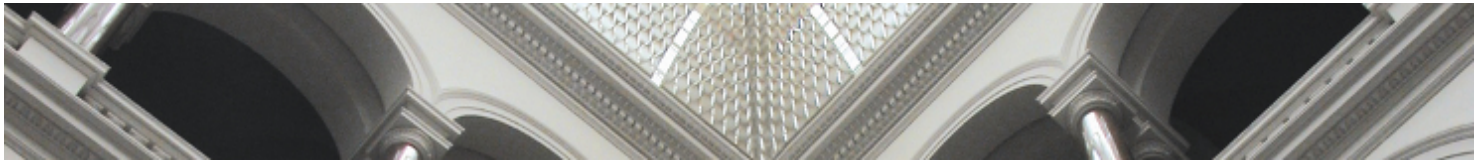
Conclusion

- **Deep and LSTM-type RNNs** have more explainable predictions.
- **Stationary dropout** could improve model's explainability.
- Explainability of RNNs should be considered in two aspects:



- **Coarse-gained**: relevance quantities adequately propagated to relevant steps
  — solution: better recurrent mechanism (i.e. LSTMs)
- **Fine-gained**: soundness of each step's explanation
  — solution: choice of input layers (i.e. convolution and pooling layers for image data)



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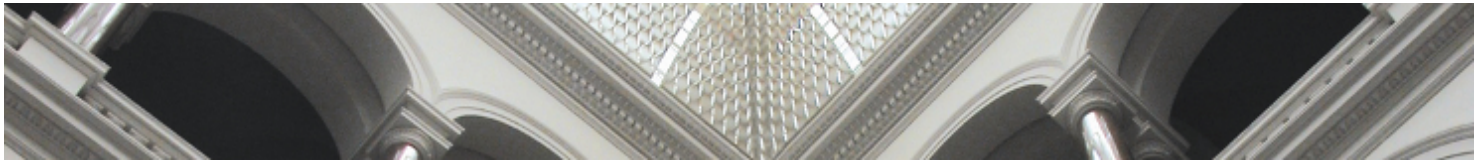
Q&A

- Part of this work is in

  Rieger, L., Chormai, P., Montavon, G., Hansen, L. K., & Müller, K. R. (2018). **Structuring Neural Networks for More Explainable Predictions.** In *Explainable and Interpretable Models in Computer Vision and Machine Learning* (pp. 115-131). Springer, Cham.

- Code can be found at **bit.ly/pat-thesis-repo**.



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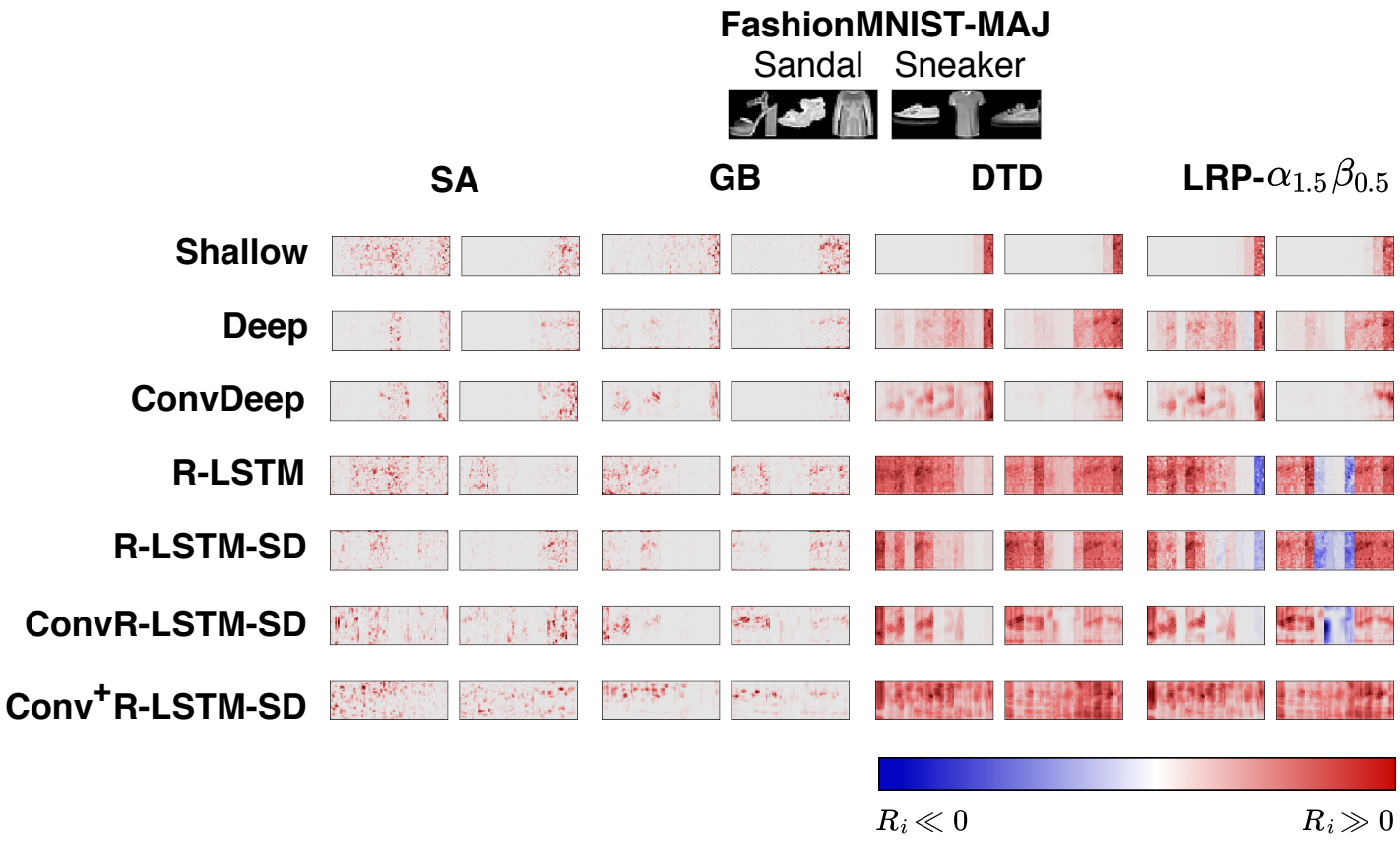
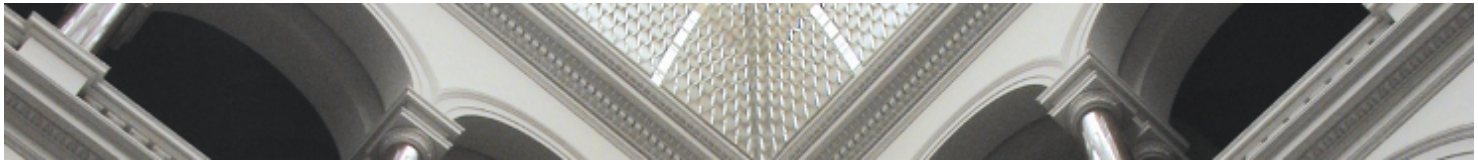
FashionMNIST Heatmaps





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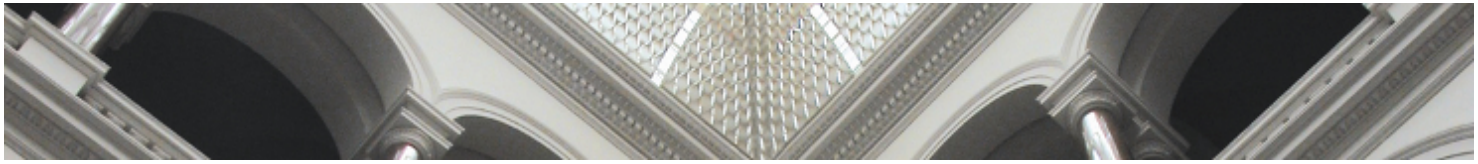
Model Accuracy

dataset	architecture	count	avg_acc	std
mnist-maj	shallow	7	98.35	0.2393
mnist-maj	deep	7	98.43	0.0926
mnist-maj	convdeep	7	99.28	0.0737
mnist-maj	rlstm	7	98.77	0.0603
mnist-maj	rlstm_sd	7	98.75	0.1248
mnist-maj	convrlstm_sd	7	99.60	0.0467
mnist-maj	convlateral_rlstm_sd	7	98.30	0.1842
fashion-maj	shallow	7	92.30	0.2550
fashion-maj	deep	7	91.35	0.3053
fashion-maj	convdeep	7	94.19	0.2128
fashion-maj	rlstm	7	93.40	0.2714
fashion-maj	rlstm_sd	7	93.42	0.2513
fashion-maj	convrlstm_sd	7	95.44	0.1356
fashion-maj	convlateral_rlstm_sd	7	89.71	0.4215



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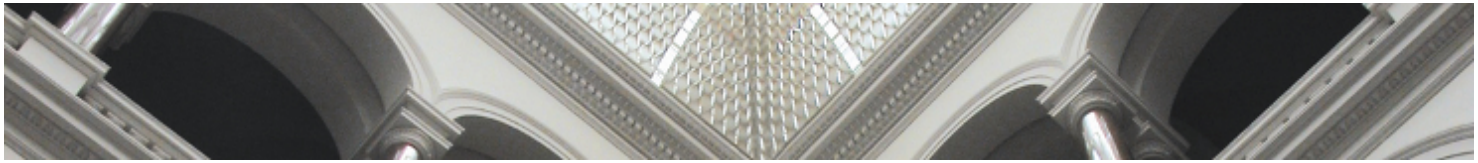

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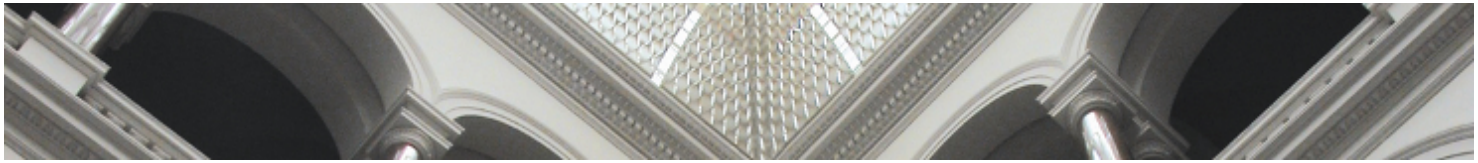

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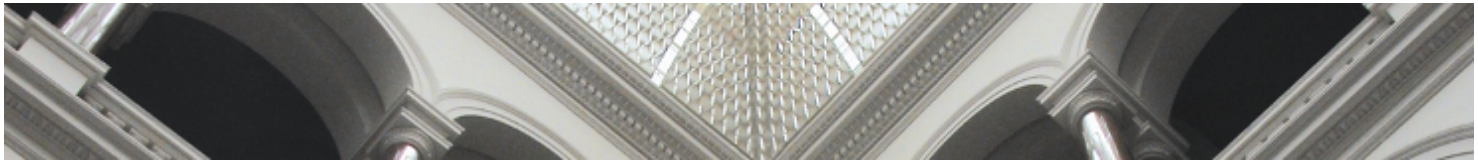

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