Benchmark for Recurrent vs. Deep Feedforward Neural Networks

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Motivation

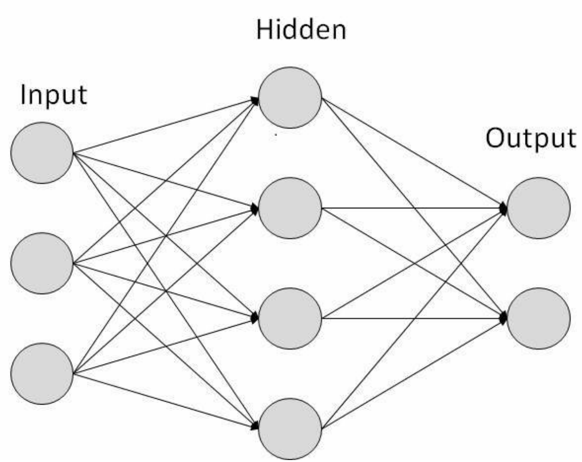
- Compare FFNN's and RNN's
- Preprocess the datasets based on scientific reasoning
- Narrow down hyperparameters with the help of literature research
- Implement hyperparameter tuning

Problems

- Imbalance of the datasets
- Sequence Length
- Preprocessing and cleaning
- Add missing prev_prev_content_id and prev_content_id

The structure of a feed forward neural

- Simplest neural network architecture
- Input feature vectors are 1-dimensional (single vector per instance)
- Supports only forward propagation
- Consists of at least one input and one output layer
- Can contain an arbitrary amount of hidden layers
    - Rarely more than 2 (Heaton, 2015)
- No cycles or loops



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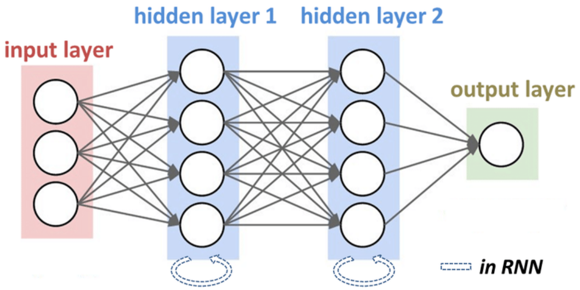
The structure of a recurrent neural network



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- Remembers multiple inputs over time (Schmidt, 2019)
- Input feature vectors are 2-dimensional (sequence of vectors)
- Contains at least one input layer and one output layer, similar to FFNN
- Recurrence through backpropagation through time in hidden layers
  - Hidden layers utilize all timestamps of an input
- Capable of capturing temporal dependencies through feedback loops

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Applied preprocessing steps

- Embedding layers for categorical id values (Heaton, 2019)
- Feature Selection
- Feature Encoding
    - One-hot encoding
    - Ordinal encoding (Potdar et al., 2017)
    - Cyclical encoding (Van Wyk, 2022)
    - Scaling
- Adding prev_prev and prev content id's
- Train-, test- and validation split (Roshan, 2022)
- Handling of missing values
- Removal of low appearing content id's
- Removal of the last record of every session
- Deciding on a sequence length
- Add padding to the recurrent neural network (Dwarampudi & Subba Reddy, 2019)
    - Pre- and post sequence padding
    - Pre- and post sequence truncation

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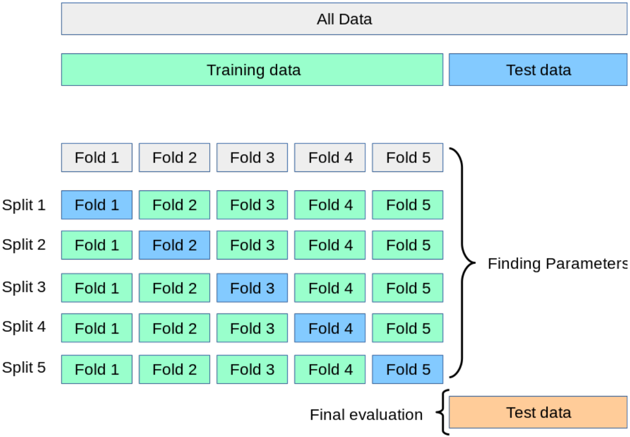
Different hyperparameters

- Number of hidden layers (Heaton, 2015)
- Number of neurons (Heaton, 2015)
- Activation function (Sharma et al., 2017)
- Loss function (Chollet et al., 2015)
- Learning rate (Bengio, 2017)
- Optimizers (Choi et al., 2020)
- Batch Normalization (Bjorck et al., 2018)
- Dropout and Dropout rate (Srivastava et al., 2014)
- Batch size (Bengio, 2018)
- Epochs (Brownlee, 2018)

Cross validation

- Each fold gets used as test fold a single time
- Each fold gets used $n-1$ times as training fold
- Data Resampling method to evaluate the ability to classify previously unseen data (Berrar, 2018)
- Higher number of folds can lead to a low bias with a high variance (overfitting) (Kohavi, 1995)
- Lower number of folds can lead to a high bias with a low variance (underfitting) (Kohavi, 1995)



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Implementation

- Implemented in python 3.12 and its well known libraries
  - pandas, numpy, scikit-learn, category_encoders, scipy, matplotlib, keras, tensorflow, optuna
- A package with 12 different subclasses
  - Each responsible for a specific subtask
- Mutliple feed forward and recurrent neural networks
  - Different types of Models
    - Preprocessed Datasets
    - No weather data
    - Only prev_prev_content_id, prev_content_id, content_id and session_id

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Results with preprocessed datasets

	# of content id's	# of sessions id's	# of samples	FFNN Accuracy	RNN Accuracy
small_original	24	79	173	51%	50%
large_original	49	74	284	25%	0%
large	53	118	284	26%	0%
large no_search	5	121	337	79%	38%
medium	215	955	8280	49%	16%
medium no_search	13	955	8331	82%	83%
small	24	36	127	37%	44%
small no_search	3	36	135	87%	100%
hotel s	86	142	947	51%	50%
hotel s no_search	8	142	995	85%	80%
hotel w	66	129	912	33%	45%
hotel w no_search	6	132	952	93%	91%

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Results with special sub datasets

	FFNN Accuracy	RNN Accuracy
small_original	49%	82%
large_original	25%	4%

Table: Results of the neural networks without weather data

	FFNN Accuracy	RNN Accuracy
small_original	24%	75%
large_original	37%	25%

Table: Results of the neural networks with only content_id, prev_content_id, prev_prev_content_id and session_id as features

	Accuracy
small_original	82%
large_original	0%

Table: Results of the recurrent neural networks without the prev and the prev_prev_content_id

Interpretation of the results

- No_search datasets significantly outperform the other variant of the dataset
  - No_search datasets have far less unique content id's
  - Otherwise these datasets are the same
- $9/10$ no_search dataset result in good model (accuracy $>= 70\%$)
  - None of other datasets exceed 51% with weather data
- FFNN's and RNN's have very similar results for most of the datasets
- Special subdatasets impact the RNN's in a more positive way

Lessons learned

- Improved knowledge about FFNN’s and RNN’s
- Hyperparameter tuning using libraries like Keras Tuner and Optuna
- Cleaning and preprocessing of datasets
  - The importance of these steps to achieve good neural networks

Techdemo

`https://github.com/RogueRefiner/BachelorThesis`

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