A Machine Learning Approach for Syllogistic Reasoning

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Syllogisms

No researchers are gods
Some gods are great reasoners
What (if anything) follows?

- Quantified statements in one of four moods (*All*, *Some*, *Some … not*, and *None*)
- Classical syllogisms consist of two premises and one conclusion
- The premises contain terms that can be arranged in one of four so-called figures
- Structurally, there are 64 possible syllogisms
- First-Order Logics is not able to account for human performance

Encodings

- Automated modeling approaches benefit from rich data
- Categorical data is not suited for numerical methods
- Standard encodings such as *onehot encoding* make categories accessible
- A syllogistic answer can be encoded using 9 bits:

All		Some		Some not		None		NVC
ac	ca	ac	ca	ac	ca	ac	ca	
0	0	1	0	0	0	0	0	0

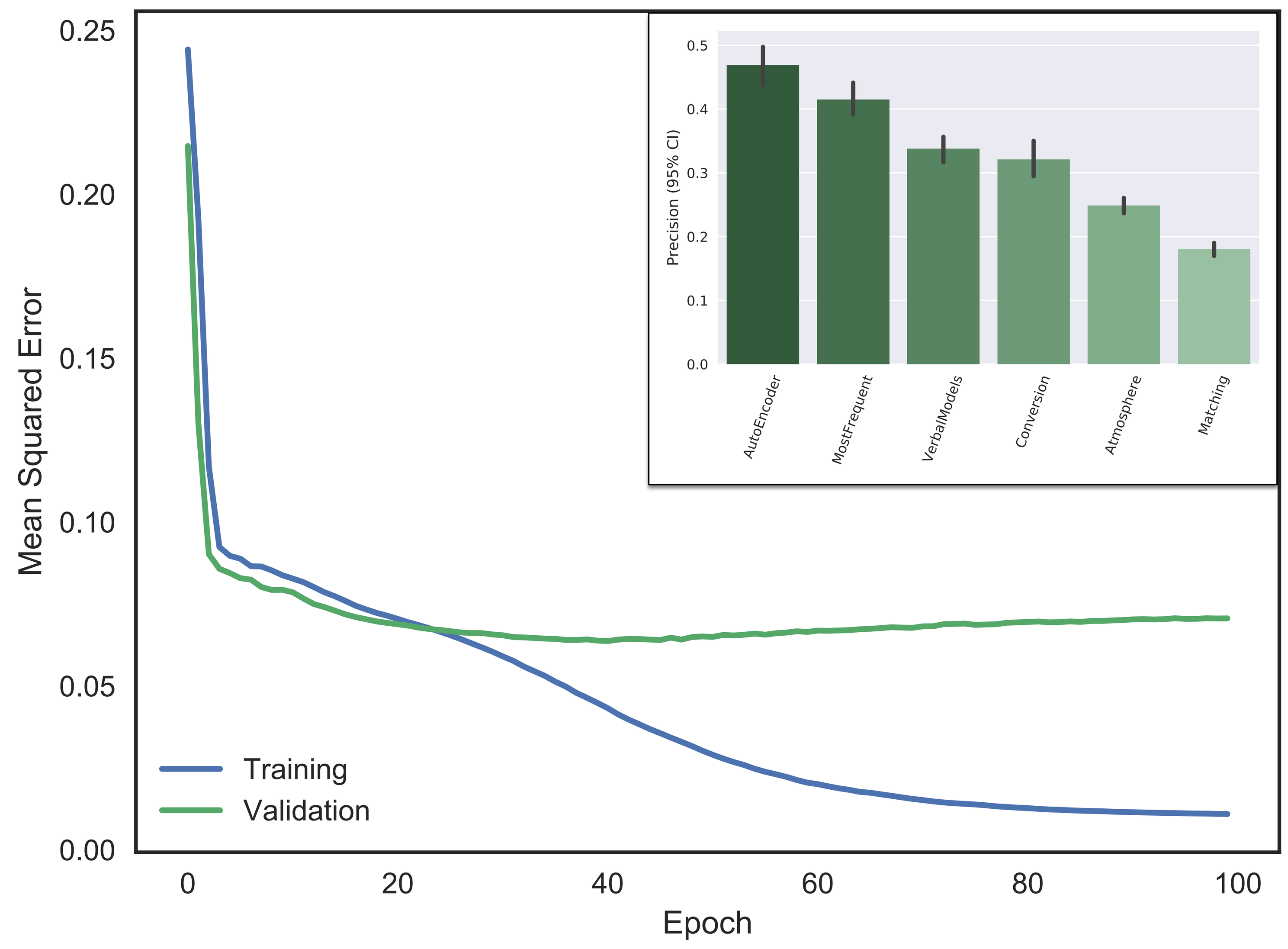
- The usual experimental record of 64 answers produce a sparse onehot vector of dimensionality 576

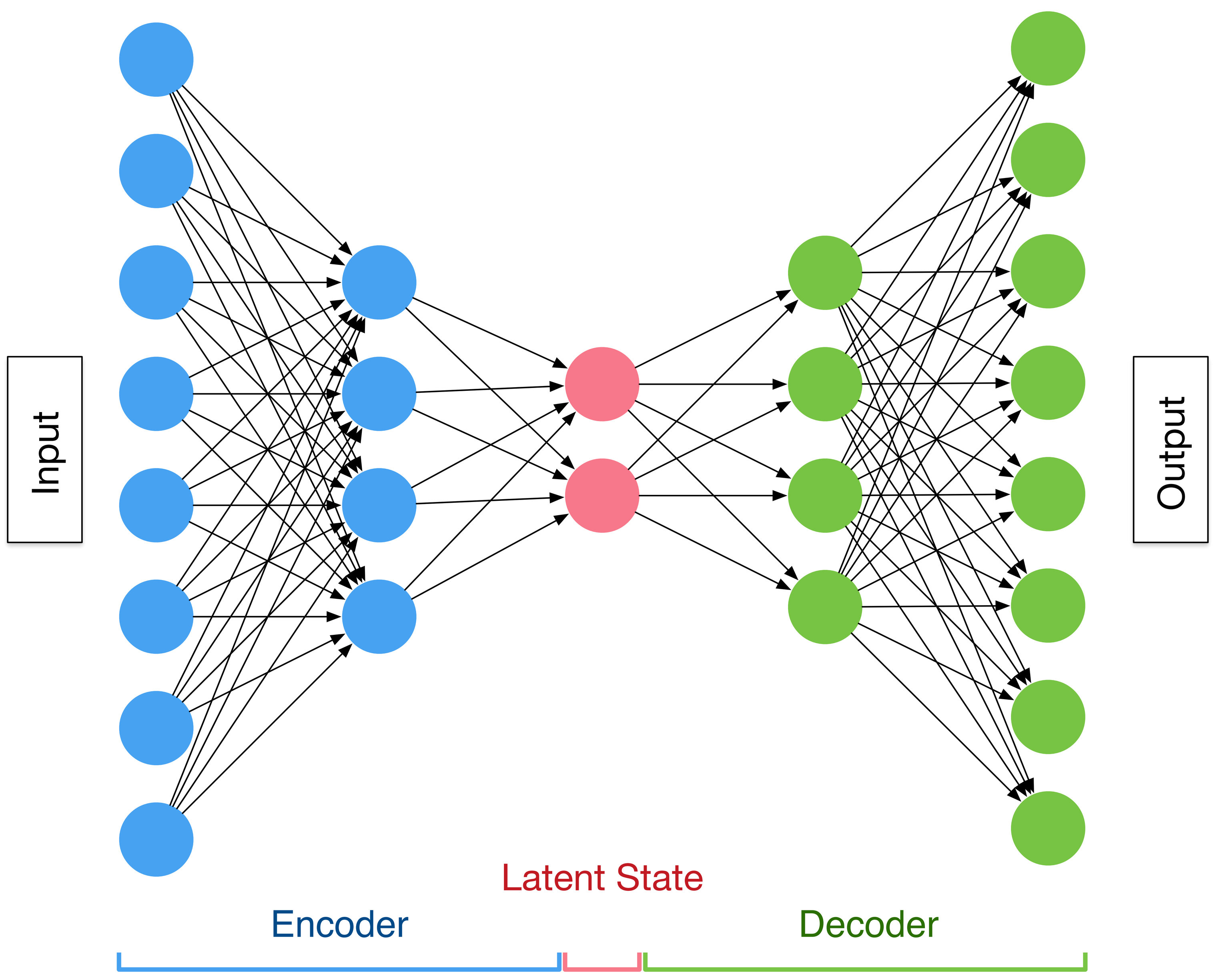
Research Question

- Does the representation of data have an impact on general model performance?
- Which features of the data are important/necessary?
- How dense is the information encoded in the data?
- Can we find encodings for behavioural data enabling the use of general models from computer science and artificial intelligence?
- Is machine learning generally suited to analyze behavioral data?
- Can we use representation learning techniques to infer meta-information from the data (e.g., dependencies, redundancies, noise, etc.)?

The Autoencoder

- Artificial neural network model finding minimized latent state representation for given inputs
- The *Encoder* component represents a function to compress the inputs into a latent state
- The *Decoder* component recovers the original data from the latent state
- Trained via general gradient descent optimization algorithms
- After training, encoder and decoder can be applied independently
- Applied to reasoning data, the autoencoder can be used to find dense latent representations of data





Conclusions

- Neural networks are capable of learning from reasoning data
- The autoencoder manages to substantially compress the data (576 to 42)
- The results suggest that behavioral data in its categorical form is highly sparse
- By finding optimized representations, it might be possible to increase general model performance
- In prediction tasks, the autoencoder is able to recover 50% missing data with a state-of-the-art precision of 48% (random baseline of 11%)
- Individual patterns can be exploited (better performance than just following the most frequent answer)
- Autoencoder can be used as baseline model for future evaluations

References

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